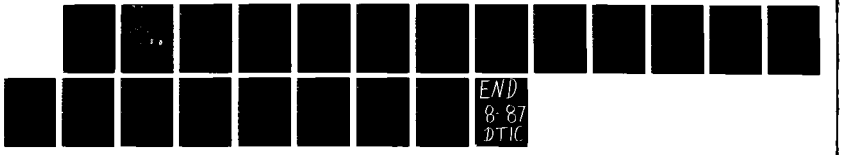
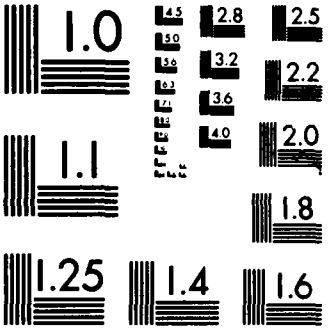
AD-A182 745 ACTIVE AMBIGUITY REDUCTION: AN EXPERIMENT DESIGN APPROACH TO TRACTABLE UU..(U) ILLINOIS UNIV AT URBANA COLL OF ENGINEERING S RAJAMONEY ET AL. 20 APR 87 1/1

UNCLASSIFIED UILU-ENG-87-2225 N00014-86-K-0309 F/G 12/9 NL






MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

DTIC FILE_COPY

April 1987 UILU-ENG-87-2225

COORDINATED SCIENCE LABORATORY
*College of Engineering*

(2)

AD-A182 745

# ACTIVE AMBIGUITY REDUCTION: AN EXPERIMENT DESIGN APPROACH TO TRACTABLE QUALITATIVE REASONING

DTIC ELECTE JUL 2 8 1987 S D C&D

**Shankar A. Rajamoney**
**Gerald F. DeJong**

UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

Approved for Public Release. Distribution Unlimited.

# REPORT DOCUMENTATION PAGE

A182745

| | |
|---|---|
| 1a. REPORT SECURITY CLASSIFICATION<br>Unclassified | 1b. RESTRICTIVE MARKINGS<br>None |
| 2a. SECURITY CLASSIFICATION AUTHORITY | 3. DISTRIBUTION/AVAILABILITY OF REPORT<br>Approved for public release; distribution unlimited |
| 2b. DECLASSIFICATION/DOWNGRADING SCHEDULE | |
| 4. PERFORMING ORGANIZATION REPORT NUMBER(S)<br>UILU-ENG-87-2225 | 5. MONITORING ORGANIZATION REPORT NUMBER(S) |
| 6a. NAME OF PERFORMING ORGANIZATION<br>Coordinated Science Lab<br>University of Illinois<br>6b. OFFICE SYMBOL (If applicable)<br>N/A | 7a. NAME OF MONITORING ORGANIZATION<br>Office of Naval Research |
| 6c. ADDRESS (City, State, and ZIP Code)<br>1101 W. Springfield Ave.<br>Urbana, IL 61801 | 7b. ADDRESS (City, State, and ZIP Code)<br>800 N. Quincy St.<br>Arlington, VA 22217 |
| 8a. NAME OF FUNDING/SPONSORING ORGANIZATION<br>Office of Naval Research<br>8b. OFFICE SYMBOL (If applicable) | 9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER<br>N00014-86-K-0309 |
| 8c. ADDRESS (City, State, and ZIP Code)<br>800 N. Quincy St.<br>Arlington, VA 22217 | 10. SOURCE OF FUNDING NUMBERS<br>PROGRAM ELEMENT NO. / PROJECT NO. / TASK NO. / WORK UNIT ACCESSION NO. |

11. TITLE (Include Security Classification)
ACTIVE AMBIGUITY REDUCTION: An Experiment Design Approach to Tractable Qualitative Reasoning

12. PERSONAL AUTHOR(S)
Rajamoney, Shankar and DeJong, Gerald

| 13a. TYPE OF REPORT | 13b. TIME COVERED | 14. DATE OF REPORT (Year, Month, Day) | 15. PAGE COUNT |
|---|---|---|---|
| Technical | FROM _____ TO _____ | April 20, 1987 | 17 |

16. SUPPLEMENTARY NOTATION

| 17. COSATI CODES | | | 18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number) |
|---|---|---|---|
| FIELD | GROUP | SUB-GROUP | Qualitative Reasoning, Experiment Design, Resolving Ambiguity. |
| | | | |
| | | | |

19. ABSTRACT (Continue on reverse if necessary and identify by block number)

Ambiguity is a limiting obstacle to qualitative reasoning systems. In this paper, we present a new approach called *active ambiguity reduction* to deal with this problem. Active ambiguity reduction involves the purposeful alteration of the world to generate new information. This new information will be inconsistent with some of the ambiguous situations, thereby eliminating them from further consideration. Active ambiguity reduction may also be viewed as *experiment design*. This paper presents a theory of experiment design which is based on the principle of *refutation*. The theory describes three strategies for designing experiments - *elaboration*, *discrimination* and *transformation*. The theory and an experiment engine - an implementation of the theory - are illustrated using a detailed example which uses qualitative reasoning tasks like determining activity, envisionment and measurement interpretation. Importantly, the experiment engine is general and domain-independent and therefore readily integrable with existing qualitative reasoning systems.

| 20. DISTRIBUTION/AVAILABILITY OF ABSTRACT | 21. ABSTRACT SECURITY CLASSIFICATION |
|---|---|
| ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT. ☐ DTIC USERS | Unclassified |
| 22a. NAME OF RESPONSIBLE INDIVIDUAL | 22b. TELEPHONE (Include Area Code) / 22c. OFFICE SYMBOL |

DD FORM 1473, 84 MAR — 83 APR edition may be used until exhausted. All other editions are obsolete.

*Technical Report*

UILU-ENG-87-2225

# ACTIVE AMBIGUITY REDUCTION:

## An Experiment Design Approach to Tractable Qualitative Reasoning *

Shankar A. Rajamoney†
Gerald F. DeJong

Artificial Intelligence Research Group
Coordinated Science Laboratory
University of Illinois at Urbana-Champaign
Urbana, IL 61801

Accesion For
NTIS CRA&I
DTIC TAB
Unannounced
Justification
By
Distribution /
Availability Codes
Dist | Avail and / or Special
A-1

April 1987

QUALITY INSPECTED 4

**ABSTRACT**

Ambiguity is a limiting obstacle to qualitative reasoning systems. In this paper, we present a new approach called *active ambiguity reduction* to deal with this problem. Active ambiguity reduction involves the purposeful alteration of the world to generate new information. This new information will be inconsistent with some of the ambiguous situations, thereby eliminating them from further consideration. Active ambiguity reduction may also be viewed as *experiment design*. This paper presents a theory of experiment design which is based on the principle of *refutation*. The theory describes three strategies for designing experiments - *elaboration*, *discrimination* and *transformation*. The theory and an experiment engine - an implementation of the theory - are illustrated using a detailed example which uses qualitative reasoning tasks like determining activity, envisionment and measurement interpretation. Importantly, the experiment engine is general and domain-independent and therefore readily integrable with existing qualitative reasoning systems.

* This research was partially supported by the Office of Naval Research under grant N-00014-86-K 0309.

† University of Illinois Cognitive Science/Artificial Intelligence Fellow.

# Active Ambiguity Reduction:

## An Experiment Design Approach to Tractable Qualitative Reasoning

### I INTRODUCTION

Qualitative reasoning systems encounter ambiguity [de Kleer79, Kuipers84] due to the qualitative nature of the reasoning and the local nature of the reasoning algorithms. Ambiguity is often a limiting obstacle to qualitative reasoning systems. Even simple world descriptions can lead to an unmanageable number of possibilities. Further, the ambiguity problem becomes dramatically worse with increased complexity of the world. Humans, not having the infallible bookkeeping abilities of computers, are overwhelmed by far fewer numbers of ambiguities. One human method to combat growing ambiguities is to actively interact with their environment. The interactions yield new data from the world which may eliminate ambiguities. Even when there are relatively few possible qualitative states, active pruning may be desirable. Humans often perform cheap tests to head off undesirable possibilities. They heft a snowball several times before throwing it or test the swimming pool temperature with a toe before diving in.

We propose a method called *active ambiguity reduction* as a partial solution to the problem of controlling ambiguities in qualitative reasoning systems. Active ambiguity reduction involves purposeful alteration of the world in such a way that observable behavior will dictate which of a number of ambiguities corresponds to reality. This process can be looked upon as conducting experiments in the world. The outcome of these experiments provide additional data which, provided the experiments are suitably chosen, will be inconsistent with a number of ambiguous qualitative scenarios. These ambiguities can then be dropped from further consideration.

Central to active ambiguity reduction is the issue of experimental design. The experimental design process must have several important features. First, it must be complete; if there is a way to tease apart an ambiguity the design system should find it. Second, it must be tolerant of

unavailable data. Third, it should be efficient. Each experiment should evenly divide the ambiguities so that significant information is acquired regardless of the experiment's outcome. Fourth, it should be practical. Lighting a match is not a reasonable way to tell whether a nearby barrel contains water or gasoline.

This paper presents a theory of experiment design that is applicable to a wide variety of qualitative reasoning tasks - determining activity, prediction and envisionment, measurement interpretation, design, and fault diagnosis and troubleshooting. This theory includes three strategies for designing experiments - *elaboration*, *discrimination* and *transformation*. The theory and an experiment engine - an implementation of the theory - are illustrated using a detailed example that involves qualitative reasoning tasks like determining activity, measurement interpretation and prediction.

## II A MODEL OF EXPERIMENT DESIGN

The ideal experiment design system accepts a set of hypotheses, designs a series of experiments and returns the "correct" hypothesis i.e. a hypothesis that is consistent with reality. An external problem solver generates the hypotheses in the course of its problem solving and uses the experiment design system to find the correct hypothesis. For qualitative reasoning, the problem solver is the qualitative reasoning system and each hypothesis is a collection of assumptions that leads to ambiguity. The experiment design system interacts with an inference system which generates a (possibly incomplete) set of predictions that are supported by a hypothesis for a given scenario. The experiment system manipulates the hypotheses and predictions to find the correct hypothesis.

The goal of experimentation is to increase the system's knowledge about a situation. If everything that can be known about the situation is already known then experimentation will not help in finding the correct hypothesis. In such a case the situation is inherently ambiguous. However, in most situations, what is known is considerably less than what is predicted by the hypotheses. Therefore, designing experiments to find out what is not known about the situation can

help in finding the correct hypothesis.

The underlying principle behind experimentation is the *refutation* of hypotheses. Experiments are designed with the specific purpose of finding information that is not compatible with the predictions of a hypothesis. When all hypotheses but one have been eliminated then the remaining hypothesis is the correct one. This principle of refutation is superior to the principle of *confirmation* of a hypothesis which involves verifying that every prediction supported by the hypothesis is correct. This is because some hypotheses may support an infinite set of predictions and therefore can never be completely confirmed. The strategies used to design experiments to refute hypotheses are described in detail in the next section.

A practical experiment design system has limitations in its ability to design all the appropriate experiments required to identify the correct hypothesis. Even after the complete space of experiments that can be designed by the system has been exhausted, there can be more than one hypothesis remaining that are consistent with the available information. Any or all of these hypotheses may be used for further problem solving since they are equivalent. However, for a given domain it may be possible to find criteria called *hypothesis selection criteria* for selecting a "best" hypothesis from the set of hypotheses left after experimentation. For example, such criteria may be based on the principle of Occam's razor that prefers "simple" hypotheses.

### A. Strategies for Experiment Design

Three strategies for designing experiments to refute hypotheses - elaboration, discrimination and transformation - are described:

**[a] Elaboration:**

In a given domain, there are usually some quantities that are readily observable or easily measurable. *Elaboration* involves observing or measuring the values of such quantities for a given scenario and refuting hypotheses that predict values for the quantity that are not compatible with the measured value. This strategy does not guarantee that the designed experiment will refute a hypothesis since all the hypotheses may support the observed value

or may be agnostic about the value of the quantity. This strategy therefore involves a tradeoff between the ease of designing an experiment and the effectiveness of the experiment in refuting hypotheses.

**[b] Discrimination:**

In elaboration the quantity to be measured is selected according to the ease with which it can be measured. This condition can be waived and elaboration can be used as the sole strategy for designing experiments. In this case, elaboration experiments result in a gradual increase of what is known about a scenario until every quantity that can be measured has been measured. However, this is very inefficient and will result in a large number of experiments that do not refute any hypothesis. In *discrimination* a quantity is selected only if its measurement will help in the refutation of hypotheses. Discrimination involves the measurement of a quantity which satisfies two criteria: 1) a number of different hypotheses should predict different values for the quantity 2) these values should be *discriminable* i.e. a measurement should be able to distinguish the different values. A quantity that satisfies these two criteria is called a *discriminant*. Once a discriminant has been selected an experiment to measure its value will result in the refutation of hypotheses that supported the other values. A discrimination experiment is guaranteed to refute hypotheses if the values of the discriminant can be grouped into sets of discriminable values and each set has at least one hypothesis that predicts a value from that set. Discrimination is more effective than elaboration since the experiments are directed towards the measurement of those quantities that will help in the refutation of hypotheses.

**[c] Transformation:**

Elaboration and discrimination select quantities from a specified scenario for measurement. However, even after the space of measurable quantities for the scenario has been exhausted it may not be possible to identify the correct hypothesis. The ability to refute hypotheses is greatly enhanced if the experiment design system is endowed with the capacity to construct

new scenarios or modify existing ones. This requires the use of domain-specific operators called *scenario transformation operators* that construct a scenario from a given scenario or propose changes to the given scenario. The ability to generate new scenarios helps in the refutation of hypotheses in two ways:

(1) The techniques of elaboration and discrimination can be applied to the new scenario. This results in the refutation of hypotheses that predicted the same value or indiscriminable values for a quantity in the original scenario and now predict different or discriminable values for the same quantity in the new scenario. This divergence of indiscriminable values can be used to select the appropriate transformations to be applied to the original scenario.

(2) A new technique called *differential discrimination* can be applied to the new scenario and the original scenario. Differential discrimination involves the measurement of a quantity that satisfies the following two criteria: 1) there are a number of hypotheses that predict the same value or indiscriminable values for the quantity in the original and transformed scenarios 2) however, the manner in which the value or indiscriminable values was reached under each hypothesis is different and discriminable. For example, the predictions in one scenario may be reached much faster or more of the predicted behavior may occur in the same time span as compared to the other scenario. Thus differential discrimination involves the discrimination of the second order behavior of a quantity across two scenarios. This strategy is efficient if transformations that lead to the discrimination of second-order behavior can be found. Then a single measurement in each scenario will refute a number of hypotheses that do not support the observed comparative behavior for the discriminant.

The problem of selecting the correct set of transformations to apply to a scenario can be viewed as a typical planning task. The initial state is the given scenario and the final state is a new scenario. The goal criterion to be satisfied by the new scenario is that it should have discriminable first-order or second-order behavior that leads to the refutation of one or more hypotheses. The plan is a sequence of transformations that converts the original scenario to a new scenario that

satisfies the goal criterion.

These three strategies are best illustrated by an example from chemistry. In chemistry, we are often asked to determine an unknown salt. The process of determining the unknown salt is called *qualitative analysis* and is done by performing a series of experiments on samples of the unknown salt. Elaboration experiments correspond to the determination of the color, taste, smell, crystalline structure, physical state, litmus test reaction etc of the given salt. These experiments are very simple to perform and are invariably carried out to get rough idea of the likely candidates. Very rarely do these experiments conclusively determine the salt. Discrimination experiments are more difficult to design and perform. For example, we might need to determine whether a precipitate has formed using centrifugal precipitation or determine the solubility of the salt by measuring the concentration of the solution using titration. Transformation corresponds to converting the salt to another compound by chemical reactions. An example of transformation and elaboration is reacting the unknown salt with concentrated HCL and checking for a precipitate and identifying the chloride formed by examining the color of the precipitate. An example of transformation and discrimination is reacting the unknown salt with NH4Cl, NH4OH and (NH4)2S and performing the borax bead test if there is a precipitate to discriminate between CoS and NiS. Transformation and differential discrimination can involve comparing the speed with which the salt reacts with a given reagent. For example, the unknown salt is reacted with NH4Cl, NH4OH, (NH4)2CO3 and CaSO4 and if there is an immediate precipitate then Ba is present, if there is a tardy precipitate Sr is present and if there is no precipitate then Ca is present.

### B. A Domain-Independent Experiment Engine

An experiment engine has been developed based on the model of experimentation described above. The inputs to the experiment engine are:

(1) A set of hypotheses.

(2) An inference engine that accepts a hypothesis and a scenario and returns a set of predictions supported by the hypothesis for the given scenario.

(3) Domain-dependent knowledge: There are three major sources of domain knowledge:

[a] A set of predicates that describe the quantities of the domain that can be measured or observed, the values that are discriminable, the parameters of a scenario that can be transformed etc. These predicates are required to design well-defined experiments that can be readily performed in the domain.

[b] A set of scenario transformation operators. These operators endow the experiment designer with the ability to construct new scenarios. A scenario transformation operator can change the quantities of some of the components of the scenario, the components of the scenario or the manner in which the components are organized. The current implementation supports only changes in the quantities of components.

[c] A set of hypothesis selection criteria. These criteria include domain specific knowledge and general principles like Occam's razor. These criteria are used to select the "best" hypothesis or hypotheses from the hypotheses remaining after experimentation.

The experiment engine uses elaboration, discrimination and transformation to design experiments. It refutes those hypotheses that support predictions that are not compatible with the results of the experiments. It finally returns the "best" hypothesis or hypotheses that are consistent with the available information.

Importantly, the experiment engine makes very few assumptions. Most qualitative reasoning systems [de Kleer84, Forbus84a, Kuipers84, Williams84] readily provide the type of inference engine that is required by the experiment design system. The domain-dependent knowledge required for designing the experiments is usually readily available. Since the experiment engine itself does not inspect the content of the hypotheses or predictions it is not limited by the domain-specific nature of the hypotheses or the predictions. Thus, the experiment engine is general and domain-independent and can be easily integrated with existing qualitative systems.

## III EXAMPLES FROM QUALITATIVE PROCESS THEORY

Qualitative Process theory (QP theory) [Forbus84a, Forbus84b] is a formalization of people's intuitive understanding of physical changes like bending, stretching, flowing, moving, boiling and colliding. QP theory characterizes these physical changes as the result of *processes*. QP theory provides a qualitative language for different types of qualitative reasoning. QP theory provides a qualitative language for different types of qualitative reasoning. QP theory also provides the framework for a number of reasoning tasks [Forbus84b] like determining activity, prediction, postdiction, measurement interpretation and skeptical analysis. Some of these are described and the advantage of using experiment design to help in the reasoning process is examined.

**[a] Determining Activity:**

The primary reasoning task is to determine the physical changes in a given situation. If there are many processes imposing conflicting changes on a quantity then the qualitative nature of the reasoning will lead to ambiguity about the resulting change. For example, evaporation, condensation and flow of liquid out of a container can each change the level of the liquid in the container. QP theory will not be able to establish whether the level is increasing, decreasing or constant unless it has further information to determine which process/es dominate/s. Experiments can be designed to measure such ambiguous quantities. In addition to resolving the ambiguity, the information from the experiments about the inequalities can help in further reasoning.

**[b] Prediction:**

Prediction involves determining how the scenario evolves with time. If there is ambiguity in determining activity or if the initial scenario was incompletely specified then prediction will result in an *envisionment* [de Kleer77, Forbus84b] - a set of possible paths into which the scenario can develop. Envisionment can lead to a potentially very large number of possible situations. Experiment design can help in curbing the combinatorial explosion by resolving ambiguities and generating information to eliminate possible situations. For example, if a

mixture of alcohol and water is heated and if the system does not know whether the boiling point of alcohol is greater than, less than or equal to that of water then it will generate situations in which alcohol boils first, water boils first and both boil together. An experiment that determines the boiling points of alcohol and water or one that examines the liquid remaining in the container or the vapor produced by boiling will help in determining which situation actually occurs. If this were a small part of a bigger computation, for example, understanding the functioning of a complex distillation factory, the information obtained by performing such experiments will considerably reduce the computational complexity.

**[c] Measurement Interpretation:**

Measurement interpretation [Forbus83, Forbus84b, Forbus86b] involves determining the changes taking place from a set of observations and an incomplete description of an initial scenario. For example, if the system is given a process vocabulary that includes evaporation, absorption and flow of liquids and is shown a scenario in which the level of the liquid in a container is decreasing then measurement interpretation determines which processes are acting even if information about the preconditions is missing. Typically measurement interpretation results in a set of alternate interpretations. In the previous example, liquid might be evaporating, being absorbed, be flowing out of the container or a combination of these. Experiment design can determine the correct interpretation.

## A. The Experiment Engine and QP Theory

The experiment engine requires hypotheses and an inference engine that returns a set of predictions supported by a hypothesis for a particular scenario. Hypotheses from QP theory can be combinations of two simple types - a *quantity space hypothesis* considers the possibility of a particular inequality relationship between two quantities and a *view instance hypothesis* considers the possibility of a view instance (a process or individual) being active or inactive. An inference engine that computes the predictions supported by a particular hypothesis is the Qualitative Process

Engine (QPE)* [Forbus86a]. These predictions describe the activity of view instances, inequalities between quantities and changes in quantities.

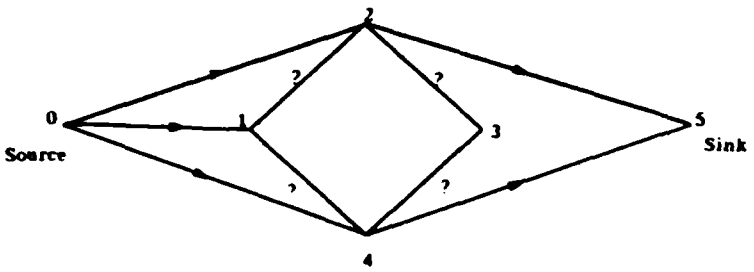
### B. An Example - A Factory with Steam Boilers

An example involving a combination of the reasoning tasks described above - determining activity, measurement interpretation and prediction - is described to illustrate the use and operation of the experiment engine. Consider a factory which uses a number of steam boilers connected by a complex network of steam pipes (figure 1a). Steam enters at the source and is fed to each of the boilers and excess steam is collected at the sink. The connecting steam pipes have adjustable valves that increase or decrease the cross-sectional area of the pipe thereby controlling the amount of flow in the pipe. Since the connecting network is complex there may be an unfortunate combination of processes that causes the pressure in one of the boilers to build up beyond the maximum capacity of the boiler leading to an explosion. The task of the qualitative reasoning system (QPE) is to guard against this possibility. The pressure in a boiler can be reduced by increasing the flow of steam out of the boiler or reducing the flow of steam into the boiler whenever the pressure in the boiler builds up dangerously.

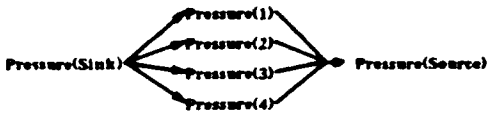
QPE can determine the direction of the active flow processes if all the pressures are available. However, there are two problems - 1) if the pressure of a particular boiler is under conflicting influences from many flow processes then the resulting change of pressure will be ambiguous and 2) if some boilers are inaccessible and all pressure measurements cannot be made then QPE will not be able to determine the arrangement of flow processes in the pipes. QPE will instead generate an envisionment of all possible scenarios that may lead to an explosion. This is unsatisfactory because the number of possible scenarios into which a scenario can develop is very large. These problems imply that a failproof system based on QPE alone will have to take preventive action for virtually every scenario. To avoid this it is advantageous to use experiment design to determine

---

* The experiment engine has not yet been integrated to the QPE. The inputs from the QPE are presently read from a file. The two programs are expected to be interfaced soon.




(a)




(b)

```
Hypothesis21: (( > Pressure(4) Pressure(3)) ( > Pressure(3) Pressure(2)) ( > Pressure(2) Pressure(1)))
Predictions: ((:Active Flow43) (:Unknown (Ds Pressure(3))) (:Increase (Ds Pressure(1))) ( > Pressure(4) Pressure(3)))
```

(c)

```
Accepting hypotheses ...
Entering experiment engine ...
Scenario = Scenario1
Performing elaboration on: ((Pressure(4) Pressure(3))
Refuting hypotheses ...
Performing discrimination on: (Ds Pressure(3))
Refuting hypotheses ...
Transforming scenario -- > (Scenario1 (:Increase (cross-sectional-area Pipe14)))
Scenario = (Scenario1 (:Increase (cross-sectional-area Pipe14)))
Performing discrimination on:      (((Dm Pressure(3)) (Dm Pressure(3)))
                                    ((Scenario1 (:Increase (cross-sectional-area Pipe14))) Scenario1))
Refuting hypotheses ...
Transforming scenario -- > (Scenario1 (:Increase (cross-sectional-area Pipe12)))
Scenario = (Scenario1 (:Increase (cross-sectional-area Pipe12)))
Performing discrimination on:      (((Dm Pressure(3)) (Dm Pressure(3)))
                                    ((Scenario1 (:Increase (cross-sectional-area Pipe12))) Scenario1))
Refuting hypotheses ...
Exiting experiment engine loop
Hypothesis21: (( > Pressure(4) Pressure(3)) ( > Pressure(3) Pressure(2)) ( > Pressure(2) Pressure(1)))
```

(d)

Figure 1: (a) A system of boilers connected by steam pipes. Boilers 1 and 2 are inaccessible. The flows in the steam pipes have to be determined. (b) The quantity space for the pressures in the system which determine the flows. The relationship between pressures 1.2.3 and 4 form the hypotheses. (c) A sample quantity space hypothesis and a sample subset of the predictions supported by the hypothesis. (d) Sample output of the experiment engine.

the active flow processes and use this information to reason about the possibility of an explosion.

Consider again the scenario shown in figure 1a in which the boilers at nodes 1 and 2 are inaccessible for pressure measurements. QPE gives the experiment engine a set of quantity space hypotheses representing the different combinations of pressure inequalities that are feasible and

consistent A specific combination yields a specific arrangement of flow processes in the pipes. The experiment engine designs experiments to find the correct combination of pressure inequalities at a given time. Based on this information, QPE can determine if an explosion is imminent and accordingly issue warnings and change the settings on the valves.

The basic cycle of the experiment engine involves constructing elaboration and discrimination experiments for a scenario. Hypotheses are refuted on the basis of the observations from the experiments. If more than one hypothesis remain then the scenario is transformed and the cycle repeats. Predictions are collected for each valid hypothesis before the experiments are designed and whenever a new scenario is created. Differential experiments are handled by discrimination where the change in the quantity is treated as a new quantity that can be used for discrimination. The experiment engine returns when only one hypothesis remains or the space of experimentation has been covered - that is, no more new measurements or scenarios are possible. In such a case if hypothesis selection criteria are available the hypothesis that best meets the criteria is returned.

Elaboration experiments are used to determine observable or readily measurable quantities. For this example, the pressure at nodes 3 and 4 represent such quantities. Let us assume that the measurement of these pressures led to the conclusion that "Pressure(3) < Pressure(4)". Therefore, the elaboration experiments lead to the refutation of the hypotheses that support the incompatible relations "Pressure(3) > Pressure(4)" and "Pressure(3) = Pressure(4)".

On examining the predictions under different hypotheses the experiment engine finds that some hypotheses predict an increase in the pressure of the boiler at node 3, others predict a decrease, still others predict no change, and the remaining hypotheses are compatible with either value. This quantity now forms the basis for discrimination since its measurement will result in the refutation of some hypotheses.

After elaboration and discrimination experiments have been performed the experiment engine is left with many hypotheses that are consistent with all the measurements made so far. It is not possible to find the correct hypothesis without modifying the original scenario. The transformable

parameters of the scenario are the cross-sectional areas of the pipes. By manipulating the valve for each pipe the system can increase or decrease the amount of flow in the pipe. The predictions obtained from the transformation of the scenario by increasing or decreasing the cross-sectional area of a pipe or a collection of pipes under each hypothesized set of pressure relationships can be obtained by *incremental analysis* [de Kleer79] or *differential analysis* [Forbus84b]. For example, QPE builds constraint networks that link the quantities of the scenario. In this case, the rate of the flow process would be constrained to be qualitatively proportional to the cross-sectional area of the pipe. By changing the cross-sectional area incrementally and traversing the constraint network the effect of the change on the measurable quantities can be found. These predictions can now be used for further elaboration and discrimination experiments. For example, for the transformation "(:Increase (cross-sectional-area Pipe14))" QPE will predict no change in the rate at which the pressure at node 4 is changing under hypotheses that include "Pressure(1) = Pressure(4)", faster increase under hypotheses that include "Pressure(1) > Pressure(4)" and slower increase under hypotheses that include "Pressure(1) < Pressure(4)". This difference can be used as the basis for differential discrimination experiments.

After all experiments have been performed the experiment engine determines the correct hypothesis. This enables QPE to determine the distribution of the flow processes in the pipes. For the set of observations given to the system for the experiments the flow processes are Flow43, Flow32, Flow21 and Flow41. QPE will find that the pressure in boiler 1 is increasing without restraint and an explosion is imminent. This will enable it to take preventive measures like decreasing the flow to boiler 1 - for example, by decreasing the cross-sectional area of pipe01.

## IV DISCUSSION

We have outlined a method to cope with certain spurious ambiguities which arise in the normal process of qualitative reasoning. The approach, called *Active Ambiguity Reduction*, would be invoked by a qualitative reasoning system confronted either with a) an unmanageably large number of ambiguous situations as might occur in constructing a full qualitative envisionment

[de Kleer79, Forbus84b], or b) some ambiguity entails an intolerable feature so that it is important for the system to discover whether this qualitative state actually corresponds to reality. When invoked, the system identifies measurements which would serve to disambiguate among the postulated alternatives. The system then proposes experiments by which these measurements can be obtained. A major portion of the research contribution addresses the problem of *experimental design*.

The current work shares a superficial similarity with the BACON system of Langley [Langley81]. While both propose experiments to gain crucial missing information, BACON does not do so in the context of a qualitative model of the world. Similarity with the later systems of NGLAUBER [Jones86] and STAHLP [Rose86] are deeper but less obvious. The purpose of these systems is theory formation and refinement and, therefore, their processing is initiated by rather different world situations. There are also important differences in internal processing. NGLAUBER uses a data-driven clustering algorithm to generate rules for observed data, and STAHLP does not perform experiments but rather relies on minimizing a cost function to decide among competing conjectures.

The current research is complementary to research in the area of fault diagnosis [Davis82, de Kleer86a, Genesereth84]. For example, the diagnostic approach described in [de Kleer86a] produces a set of candidates each of which explains the observed differences in behavior between the model and the artifact. An active ambiguity reduction module might use this set of candidates as input hypotheses. Experiments would then be designed to identify the actual fault/s in the model. An ATMS [de Kleer86b] could also be used to organize the hypotheses that are input to the AAR experiment engine. The assumptions or collections of assumptions underlying a contradiction would then form the hypotheses to be tested.

Active ambiguity reduction might also be used to complement Forbus' notion of measurement interpretation [Forbus86b]. Forbus describes how constraints from envisionment can restrict the total number of interpretations for a given set of measurements. In general, this approach results in

a number of interpretations each of which is consistent with the available measurements. The set of interpretations might be given to the AAR module as ambiguities resulting in the design of experiments to generate the additional measurements required to further reduce the set of interpretations.

In [de Kleer79] de Kleer describes two approaches to resolving ambiguities - 1) using quantitative information and 2) using teleological arguments. The AAR approach operates within the framework of qualitative reasoning. However, teleological information can also be used if it is input as either one of the predictions supported by the hypotheses or as a hypothesis selection criterion.

Continuing research includes the construction of a model of theory refinement [Mitchell86, Rajamoney87] based on Forbus' QP theory [Forbus84b]. The resulting system has a similar motivation to STAHLP [Rose86] but is experimentally oriented. Qualitative reasoning, and QP theory in particular, rely on an accurate description of all the processes of a domain. If the theory is flawed - for example, a process is missing, a precondition is incorrect, a limit point is unknown (a new landmark value [Kuipers85] is needed), or an influence is missing then discrepancies may arise between predictions of the model and observations of reality. In general there will be many different changes to the theory that remove the anomaly. Each change may result in a distinct qualitative theory. The resulting theories form a set of ambiguous hypotheses. We are extending the ADEPT system [Rajamoney85, Rajamoney86] to integrate our notions of active ambiguity reduction to experimentally determine which of the various hypotheses correspond to reality.

## ACKNOWLEDGMENTS

We would like to thank the members of the Machine Learning group at the Coordinated Science Laboratory for helpful discussions and suggestions on the research reported in this paper. We are also grateful to Ken Forbus for many helpful discussions on Qualitative Process theory.

## REFERENCES


[Davis82] R. Davis, H. Shrobe, W. Hamscher, K. Wieckert, M. Shirley and S. Polit, "Diagnosis Based on Description of Structure and Function," *Proceedings of the National Conference on Artificial Intelligence*, Pittsburgh, PA, August 1982, pp. 137-142.

[de Kleer77] J. de Kleer, "Multiple Representations of Knowledge in a Mechanics Problem-Solver," *Proceedings of the Fifth International Joint Conference on Artificial Intelligence*, Cambridge, MA, August 1977, pp. 299-304.

[de Kleer79] J. de Kleer, "The Origin and Resolution of Ambiguities in Causal Arguments," *Proceedings of the Sixth International Joint Conference on Artificial Intelligence*, Tokyo, Japan, 1979.

[de Kleer84] J. de Kleer and J. S. Brown, "A Qualitative Physics Based on Confluences," *Artificial Intelligence 24*, (1984), .

[de Kleer86a] J. de Kleer and B. C. Williams, "Reasoning About Multiple Faults," *Proceedings of the National Conference on Artificial Intelligence*, Philadelphia, PA, August 1986, pp. 132-139.

[de Kleer86b] J. de Kleer, "An Assumption-Based Truth Maintenance System," *Artificial Intelligence 28*, (1986), pp. 127-162.

[Forbus83] K. Forbus, "Measurement Interpretation in Qualitative Proces Theory," *Proceedings of the Eighth International Joint Conference on Artificial Intelligence*, Karlsruhe, Germany, 1983.

[Forbus84a] K. Forbus, "Qualitative Process Theory," *Artificial Intelligence 24*, (1984), pp. 85-168.

[Forbus84b] K. D. Forbus, "Qualitative Process Theory," Technical Report 789, Ph.D. Thesis, MIT AI Lab, Cambridge, MA, August 1984.

[Forbus86a] K. Forbus, "The Qualitative Process Engine," UIUCDCS-R-86-1288, University of Illinois, Department of Computer Science, Urbana-Champaign, 1986.

[Forbus86b] K. Forbus, "Interpreting Measurements of Physical Systems," *Proceedings of the National Conference on Artificial Intelligence*, Philadelphia, PA, August 1986, pp. 113-117.

[Genesereth84] M. R. Genesereth, "The Use of Design Descriptions in Automated Diagnosis," *Artificial Intelligence 24*, (1984), pp. 411-436.

[Jones86] R. Jones, "Generating Predictions to Aid the Scientific Discovery Process," *Proceedings of the National Conference on Artificial Intelligence*, Philadelphia, PA, August 1986, pp. 513-517.

[Kuipers84] B. Kuipers, "Commonsense Reasoning About Causality: Deriving Behavior from Structure," *Artificial Intelligence 24*, (1984), pp. 169-204.

[Kuipers85] B. Kuipers, "The Limits of Qualitative Simulation," *Proceedings of the Ninth International Joint Conference on Artificial Intelligence*, Los Angeles, CA, August 1985, pp. 128-136.

[Langley81] P. Langley, "Data-Driven Discovery of Physical Laws," *Cognitive Science 5*, 1 (1981), pp. 31-54.

[Mitchell86] T. M. Mitchell, R. Keller and S. Kedar-Cabelli, "Explanation-Based Generalization: A Unifying View," *Machine Learning 1*, 1 (January 1986), pp. 47-80.

[Rajamoney85] S. Rajamoney, G. F. DeJong and B. Faltings, "Towards a Model of Conceptual Knowledge Acquisition through Directed Experimentation," *Proceedings of the*

*Ninth International Joint Conference on Artificial Intelligence*, Los Angeles, CA, August 1985. (Also appears as Working Paper 68, AI Research Group, Coordinated Science Laboratory, University of Illinois at Urbana-Champaign.)

[Rajamoney86] S. A. Rajamoney, "Automated Design of Experiments for Refining Theories," M. S. Thesis, Department of Computer Science, University of Illinois, Urbana, IL, May 1986. (Also appears as Technical Report T-2213, AI Research Group, Coordinated Science Laboratory, University of Illinois at Urbana-Champaign.)

[Rajamoney87] S. Rajamoney and G. DeJong, "The Classification, Detection and Handling of Imperfect Theory Problems," *Proceedings of the Tenth International Joint Conference on Artificial Intelligence*, Milan, Italy, August 1987.

[Rose86] D. Rose and P. Langley, "STAHLp: Belief Revision in Scientific Discovery," *Proceedings of the National Conference on Artificial Intelligence*, Philadelphia, PA, August 1986, pp. 528-532.

[Williams84] B. Williams, "Qualitative Analysis of MOS Circuits," *Artificial Intelligence 24*, (1984)..

END

8-87

DTIC